Comparison of Global Histogram-based Thresholding Methods that Applied on Wound Images

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ABSTRACT
Image processing is used effectively in the medical field because of the convenience it brings to human life. Incorrect data which obtained during image processing operations in the medical area can have serious consequences. Therefore, the selection of the thresholding method used as pre-image processing step is also vital. In this study, comparison of image thresholding methods was performed. The selected maximum entropy, minimum error threshold, Otsu's method, simple threshold selection minimum and simple threshold selection mean methods were tested on a special data set consisting of wound images. The methods were compared using the values obtained from the selected metrics results. According to the comparison results, the most successful methods is determined as Otsu's method and maximum entropy methods for dermatologic images which have different resolutions and image qualities. The success rates of the methods are presented in the paper using the metrics results obtained.

Keywords
Thresholding, Global Histogram-Based Thresholding, Image Segmentation, Medical Image Processing, Dermatologic Images.

1. INTRODUCTION
Image segmentation is one of the important preprocessing techniques used in digital image processing. Image segmentation can also be regarded as one of the most difficult problems encountered in image analysis [1]. Image segmentation is the process of separating a scene into homogeneous and meaningful regions and objects [2]. Image thresholding is one of the most important techniques used in image segmentation studies and is often used in object tracking, pattern recognition, computer vision, object detection, and so on [3]. Motivation behind the extensive use of thresholding technique is due to its easy implementation and computationally efficient performance. Basically, thresholding is used to identify and extract a target from its background on the basis of distribution of gray levels or texture in image objects [4].

In thresholding process, the pixel value of the objects is changed to 1 and the pixel value of the background images is changed to 0. The new image is segmented using the image which is binarized by way of the thresholding process [5]. Thresholding methods [6 – 16] have applied in wide range of areas such as medical image processing [6, 13, 14], image segmentation and reconstruction [7, 10, 11], object detection and recognition [8, 12], document analysis [9], characters recognition [16] etc.

Segmentation subdivides an image into its constituent region or object. There are various applications of image segmentation like locate tumors or other pathologies, measure tissue volume, computer-guided surgery, treatment planning, study of anatomical structure, locate objects in satellite images and fingerprint recognition etc. [15]. Erroneous data obtained due to mistakes made during the thresholding process lead to incorrect results in the applications used and seriously affect the performance rates of these applications [17]. Erroneous data obtained during vital studies, especially medical image processing studies, can have serious consequences. Therefore, the selection of the thresholding method used in the pre-image processing phase is important. Thresholding has been a topic of interest for many years for many different researchers.

Rider and Calvard [18] proposed an iterative thresholding method. Prewitt and Mendelsohn [19] offered a threshold method that using histogram regions for selecting threshold value. Otsu [20] described an adaptive threshold method that is calculated using intraclass variance and interclass variance values. Otsu thresholding method that uses grey histogram is used widely. Tsai [21] proposed a thresholding method called Tsallis entropy technique which using the moment-preserving principle to select threshold. Kapur et al. [22] proposed a method that using entropy of the histogram while choosing threshold value. Qi [23] offered a method called maximum entropy threshold which is based on arithmetic gray scale variation.

Image processing techniques such as thresholding methods used in a wide range of area are also being used effectively in the medical field. However, since the images used in the medical image processing field and the decisions taken are important in such issues as disease detection, wound dressing, etc., processing of the obtained image becomes a very important factor. In this study, selected global histogram-based thresholding methods were applied on the images and the performance of the methods were determined by using Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Correlation Index (CI) and Time elapsed (TE) metrics results.

In section 2, global histogram-based thresholding methods used in the study are explained in detail. In section 3, experimental results and discussion is represented. In section 4, draws a conclusion and suggests some future works.

2. GLOBAL HISTOGRAM-BASED THRESHOLDING METHODS
There are many methods for thresholding the image. Among them, Histogram-based methods are simple, fast and easy to implement. The general logic used in these methods is that the pixels take a categorization over a specified value and the pixels that do not fit in this value remain in the other category. [13]. In the following subsections, global histogram-based thresholding methods which are selected for using in this study are described in detail.

2.1 Maximum Entropy Thresholding

Segmentation is a process used in many applications in the field of image processing. One of the frequently used methods in the segmentation is the thresholding process. The maximum entropy threshold from the thresholding methods is based on arithmetic gray scale variation [23]. To properly segment the image, the threshold value must be selected as the appropriate value for each image. The selection of the threshold by the maximum entropy method comes from Shannon's classical entropy method [24]. In Kapur's maximum entropy method, the distinction of the regions is based on the central distribution. If the object separates sharply from the background, the threshold value selected in the gray level histogram classification can be from the valley values. However, the two-peaked gray level histogram value is not easily accessible. The entropy-based thresholding technique is more effective and more important in the segmentation process. The entropy-based threshold is based on the probability distribution function of the gray level histogram. Many multi-level thresholding algorithms also use Kapur's entropy-based thresholding technique. Kapur assumes that there are two probability distributions. One belongs to objects and the other belongs to the background. To find the best threshold value, the highest value of the sum entropy of the fragmented image is selected. With this method, it is aimed to find the most suitable threshold according to Kapur's entropy technique [4]. The maximum entropy threshold is obtained by using the following (1), (2), (3) and (4).

$$\sum_{i=0}^{255} h(i) \tag{1}$$

$$H_b(t) = -\sum_{i=0}^{t} \frac{h(i)}{\sum_{j=0}^{t} h(j)} * log\ \frac{h(i)}{\sum_{j=0}^{t} h(j)} \tag{2}$$

$$H_w(t) = -\sum_{i=t+1}^{255} \frac{h(i)}{\sum_{j=t+1}^{255} h(j)} * log\ \frac{h(i)}{\sum_{t+1}^{255} h(j)} \tag{3}$$

$$T = ArgMax_{t=0......imax} H_b(t) + H_w(t) \tag{4}$$

Where *h(i)* is the normalized histogram, $H_b(t)$ is the entropy of the black pixels, $H_w(t)$ is the entropy of the white pixels, and T is the threshold value refers to the point where the sum of the white and black pixels is the maximum [22].

2.2 Minimum Error Thresholding

A grayscale histogram of an image gives us a distribution pattern of gray tones. The normalized histogram gives the frequency of the gray tones in the image. The histogram can act as a probability density distribution function for comparing distributions of object and background gray levels.

The minimum error thresholding method models the conditional probability density function according to the Gaussian distribution to classify the image as background and object. But this approach removes the assumption of change. When the error is reduced to a minimum, it is assumed that the contrast values more accurately match the model. The error function can be expressed by the criterion function. Kittler and Illingworth used the criterion function for the grayscale histogram to find the optimal threshold value [25]. The role of the criterion function is to find the threshold value where the error is minimum [26]. Minimum error thresholding is obtained by using the probability density function of the background class that follows the threshold in (5), the probability density function of the object class in (6), and the criterion function in (7) [27].

$$\int_{-\infty}^{t} P_0\,(x) d_x \tag{5}$$

$$\int_{t}^{\infty} P_b(x) d_x \tag{6}$$

$$E(t) = \ominus \int_{-\infty}^{t} P_0(x) d_x + (1 - \ominus) \int_{t}^{\infty} P_b(x) d_x \tag{7}$$

2.3 Otsu's Method

The ideal threshold for image segmentation can be determined as the valley point in the histogram with two-peak (bimodal) gray level. However, although it is ideal to create a histogram with two-peak (bimodal) distributions, this process is difficult and costly because of the noise and light distortions in the image. [20]. Threshold selection on a one-dimensional histogram is easier and less costly. Otsu's method operates on the gray level histogram.

In the Otsu's method, intraclass variance and interclass variance are calculated for all values in the gray level histogram. For the optimal threshold value, the sum variance is not considered. When the intraclass variance is minimum, the interclass variance approaches to the maximum, when the interclass variance is maximum, intraclass variance approaches to the minimum [28]. In the Otsu method, the thresholding process takes place in 3 steps [20].

1. Each tone value is divided into two parts as pre-threshold and post-threshold.

2. Using the obtained data, intraclass variance and interclass variance are calculated. These operations are performed by following (8) and (9).

   $$\sigma_G^2 = \sum_{i=0}^{N-1} \left(i - \mu_G\right)^2 P_i \tag{8}$$

   Where σ_G^2 is global variance value, m_G is the average density of the global pixels and p_i is the probability of the i value.

   $$\sigma_B^2 = P_1\left(\mu_1 - \mu_G\right)^2 + P_2\left(\mu_2 - \mu_G\right)^2 \tag{9}$$

   Where σ_B^2 gives out the intraclass variance value, μ_1 gives out the pixel density coming from the first class and μ_2 gives out the pixel density coming from the second class.

3. The image is thresholded within two calculated threshold values.

2.4 Simple Threshold Selection Minimum and Mean

The most primitive approach to threshold selection is to accept the mean or median values as a threshold. Thresholding by selecting a mean or median value in a noiseless image can be effective in separating objects and background from each other. However, in general, many of the images studied are not suitable for this situation [29]. Histogram-based thresholding is one of the popular approaches to image segmentation to make decisions based on peak and valley values [30]. If we consider the two peak points of the gray value histogram of the image, two different approaches emerge. In the first of these, while the average value of these two points is taken as the threshold value whereas the other approach is to regard the minimum value between the two points as the threshold value [31]. The threshold value obtained by taking the average of these two points according to the first approach is determined by the following (10).

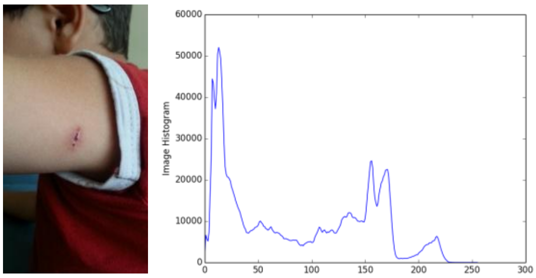
$$T = \frac{P1+P2}{2} \tag{10}$$

Where T is the threshold value, P1 is the first peak, and P2 is the second peak. According to the other approach, the threshold value obtained by taking the minimum value between of these two points is determined by the following (11).

$$T = \min H(U), \quad U \in [P1, P2] \tag{11}$$

3. EXPERIMENTAL RESULTS AND DISCUSSION

To verify the performance of our paper, a set of various images was tested by selected global histogram-based thresholding methods. The methods used in the study were implemented using the Python language. Implementation of specified methods on images is also done in Python environment. The methods were tested on a special data set that are consist of wound images which are different resolutions and image qualities taken from the patients by a dermatologist. The purpose of testing the study on a data set consisting of wound images with different sharpness and resolution is to be able to deduce the behavior of the compared global histogram-based thresholding methods on different image qualities and resolutions. In Fig. 1.(a), contains one of the images with a particularly clear wound image in the data set used in the test phase. The histogram distribution graph of the image which is used in Fig. 1.(a) is shown in Fig. 1.(b). In Fig. 2.(a) - (e), are given the results of the thresholding methods applied on the image which is shown in Fig. 1.(a).



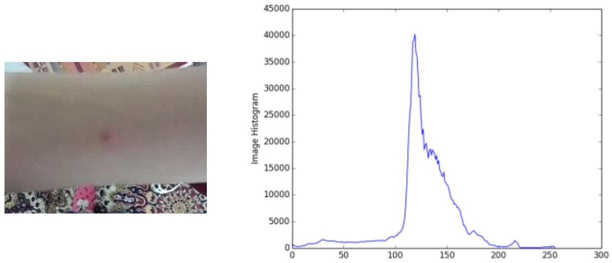
(a) **(b)**

Fig 1: (a) Original image, (b) histogram graph of image

(a) **(b)** **(c)** **(d)** **(e)**

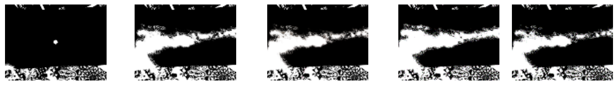
Fig 2: Test results of (a) max entropy method, (b) min. error threshold method, (c) Otsu's method, (d) simple threshold selection minimum method and (e) simple threshold selection mean method

In Fig. 3.(a) on below, contains one of the images with a particularly blurry wound image in the data set used in the test phase. The histogram distribution graph of the image which is used in Fig. 3.(a) is shown in Fig. 3.(b). In Fig. 4.(a) - (e), are given the results of the thresholding methods applied on the image which is shown in Fig. 3.(a).



(a) **(b)**

Fig 3: (a) Original image, (b) histogram graph of image



(a) **(b)** **(c)** **(d)** **(e)**

Fig 4: Test results of (a) max entropy method, (b) min. error threshold method, (c) Otsu's method, (d) simple threshold selection minimum method and (e) simple threshold selection mean method

The values obtained from result of the tests were evaluated by using the MSE, PSNR, CI metrics which are selected for this study, and the TE values of the methods were calculated as in seconds. The MSE metric is one of the common methods used in evaluating the results of studies performed in most image processing applications. Here, the expected value of the averages of the squares of the differences between the source image and the final image which comes from methods used is obtained. This process is performed by the following (12).

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[x'(i,j) - x(i,j)]^2 \tag{12}$$

Where $x'(i,j)$ is the pixel value of the image that is obtained after the thresholding, $x(i,j)$ represents the corresponding pixel value of the original image. With the MSE method, different error results can be obtained depending on the resolution of the image. Because the majority of the images used in this study consisted of high-resolution images, the result of MSE was quite high. The PSNR method gives the ratio between the maximum power of a signal and the expected value of the average of its squares. This process is performed by the following (13).

$$PSNR = -10log_{10}\frac{MSE}{S^2} \tag{13}$$

Where S^2 is the largest pixel in the image. The CI method is a value used to represent the relationship between variables. The results are between -1 and +1. Negative values indicate a negative relationship, while positive values indicate a positive relationship. When values are 1 or -1, it indicates a perfect relationship. This process is performed by the following (14).

$$CI = \frac{cov(X,Y)}{\sigma_x * \sigma_y} \tag{14}$$

Where $cov(X,Y)$ is the covariance value of the two images, σ_x is the standard deviation of the image X, and σ_y is the standard deviation of the image Y. By using the values obtained as a result of all the calculations, it was determined which conditions the results of the methods gave and the performance graph was obtained. As a result of this study, the most successful methods have been identified. Table 1 gives the mean values of TE, CI, MSE and PSNR results obtained by testing selected methods on all images. Table 2 gives the TE, CI, MSE and PSNR values obtained by testing the selected methods on the images shown in Fig. 1.(a) and Fig. 3.(a).

Table 1. TE, CI, MSE and PSNR results of max entropy, minimum error threshold, Otsu's method, simple threshold selection minimum and simple threshold selection mean methods

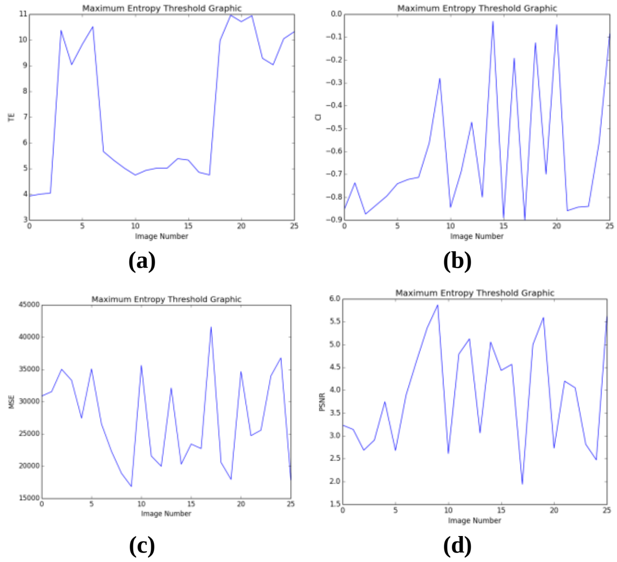
Methods	TE (sec.)	CI	MSE	PSNR (dB)
Maximum Entropy	6,7512	-0,6150	27202,3137	3,9325
Minimum Error Threshold	6,8736	-0,4800	21837,0101	4,8408
Otsu's Method	11,5120	-0,7933	28377,3982	3,7176
Simple Threshold Selection Min.	6,4012	-0,5353	22524,4553	4,7008
Simple Threshold Selection Mean	6,0765	-0,5160	21442,5772	4,7669

Table 2. TE, CI, MSE and PSNR results of max entropy, minimum error threshold, Otsu's method, simple threshold selection minimum and simple threshold selection mean methods*

Fig. No	Methods	TE (sec.)	CI	MSE	PSNR (dB)
1	Maximum Entropy	9,0485	-0,8400	33997,4428	2,8163
	Minimum Error Threshold	9,6169	-0,5251	22269,2743	4,6537
	Otsu's Method	14,2452	-0,8419	33764,0433	2,8462
	Simple Threshold Selection Mi.	8,7608	-0,5634	23293,5970	4,4584
	Simple Threshold Selection Me.	8,2824	-0,5251	22269,2743	4,6537
3	Maximum Entropy	4,7014	-0,7130	22309,7340	4,6458
	Minimum Error Threshold	4,8575	-0,6088	22447,3246	4,6191
	Otsu's Method	9,5141	-0,6223	21941,5638	4,7181
	Simple Threshold Selection Mi.	4,6552	-0,6065	22408,0740	4,6267
	Simple Threshold Selection Me.	4,2928	-0,6129	22472,1544	4,6143

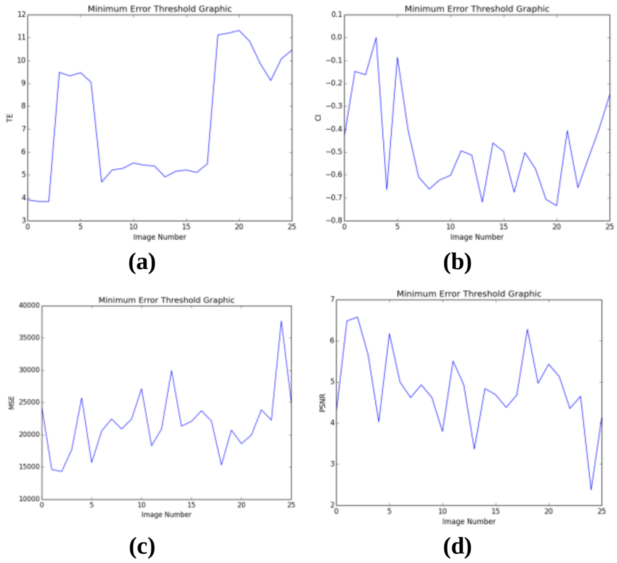
* These results are obtained from images which are shown in Fig. 1.(a) and Fig. 3.(a).

As shown in Tables 1 and 2, the performance of the thresholding methods varies depending on the resolution and sharpness of the images used. The simple threshold selection mean gives the most successful results in terms of the duration of the metrics used. But with other metrics results, its performance is low. It is observed that the Maximum entropy and Otsu's method give very successful results by looking at the resultant given by the methods tested on different resolution and sharp images which are compared in Table 2. In Fig. 5, Fig. 6, Fig. 7, Fig. 8, and Fig. 9 below, show graphs of TE, CI, MSE, and PSNR values of the methods used in the study.



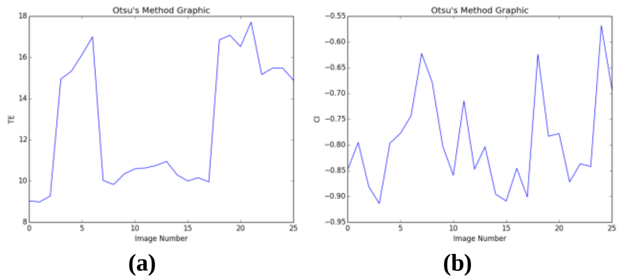
(a) (b) (c) (d)

Fig 5: Graphical display of maximum entropy threshold method's (a) TE results, (b) CI metric results, (c) MSE metric results, (d) PSNR metric results

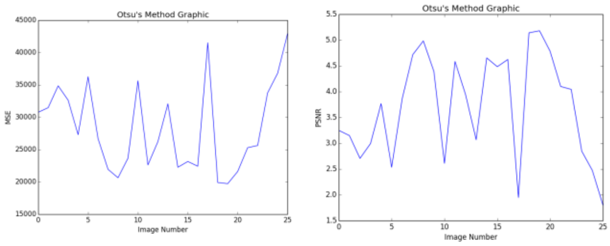


(a) (b) (c) (d)

Fig 6: Graphical display of minimum error threshold method's (a) TE results, (b) CI metric results, (c) MSE metric results, (d) PSNR metric results

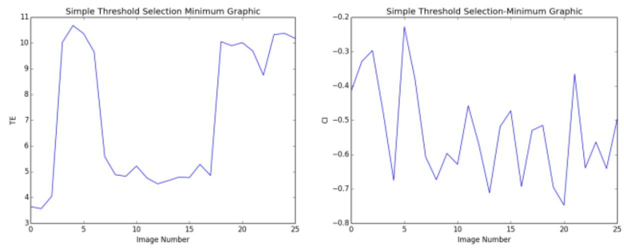


(a) (b)

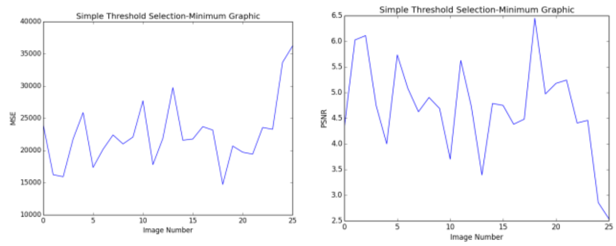


(c) **(d)**

Fig 7: Graphical display of Otsu's method's (a) TE results, (b) CI metric results, (c) MSE metric results, (d) PSNR metric results

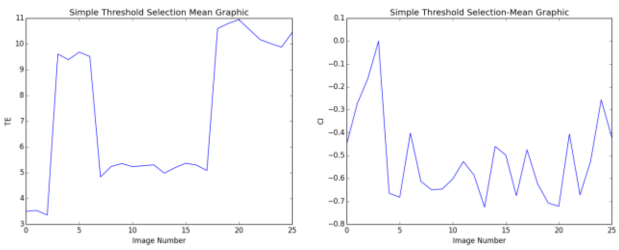


(a) **(b)**

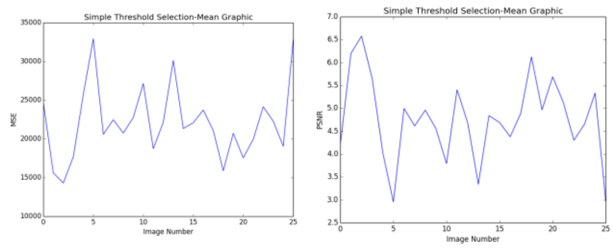


(c) **(d)**

Fig 8: Graphical display of simple threshold selection minimum method's (a) TE results, (b) CI metric results, (c) MSE metric results, (d) PSNR metric results



(a) **(b)**



(c) **(d)**

Fig 9: Graphical display of simple threshold selection mean method's (a) TE results, (b) CI metric results, (c) MSE metric results, (d) PSNR metric results

The graphical representation of MSE values of maximum entropy, minimum error threshold, Otsu's method, simple threshold selection minimum and simple threshold selection mean methods is given in Fig. 10.

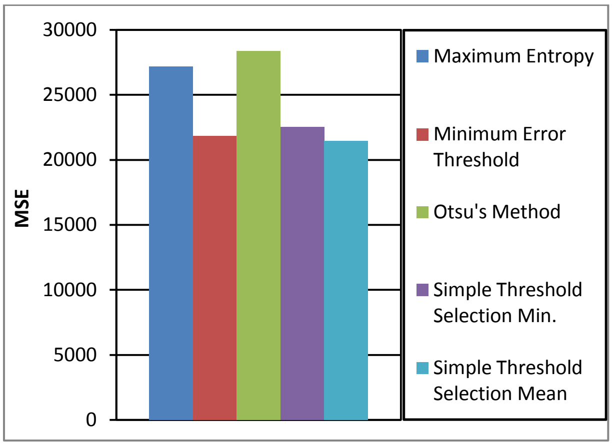


Fig 10: MSE results of applied maximum entropy, minimum error threshold, Otsu's method, simple threshold selection minimum and simple threshold selection mean methods

4. CONCLUSIONS AND FUTURE WORKS

In this study, the comparison of image thresholding methods which are frequently used in the fields such as medical image processing, pattern recognition, object detection etc. has been realized. The selected maximum entropy, minimum error threshold, Otsu's method, simple threshold selection minimum and simple threshold selection mean methods were tested on a special data set consisting of wound images with different resolution, sharpness and light conditions used in the study. The performance analysis of the methods was carried out by comparing the results obtained via the determined TE, CI, MSE and PSNR metrics.

Based on the results obtained, it has been found that the process of extracting the wounds is most successfully accomplished by Otsu's method and maximum entropy methods in images where light is inadequate, the image is not clear or where there is little difference in density between areas is desired to be separated on images.

The results obtained from this study will shed light on the work to be done in future studies in the selection of the thresholding method on medical images. At the same time, unnecessary waste of time can be avoided by saving the time spent to see what methods and results on medical image to work.

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